

# Auction Price Prediction & Image Features

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# Auction Process



Item on sale



Bidding



Highest price

**Buyer's premium**

## Project goals



## Sellers

Price prediction

Advertising

Estimate vehicle value

Auction arrangement

Interpretability

Increase  
expected price

Fix or not fix



Preprocess Data

Feature  
Extraction

Image  
Processing

Image  
Annotation

Final Model

Various Modelling Attempts

# Timeline

# Preprocess Data

## Tabular Data

- Final auction price
- Make, Year, Mileage, etc.

## Text Data

- Tire, bucket, engine, etc.



Extract  
Features!

Non-annotated

# Feature: Colorfulness Scores

10 Most Colorful



10 Least Colorful



# Feature: Text Sentiment

## VADER

- ❖ Lexicon and rule-based sentiment analysis tool
- ❖ Preceding tri-grams (observe 90% negation flip); Conjunctions

### Engine (more than 100 characters' comments)

Engine access door latch area **damaged**, engine knocks, engine shroud **damaged**, new holland 450nc 5.01 four cylinder diesel engine

81 hp, approximately one hour on replaced engine, new holland 445m2 four cylinder diesel engine, recently replaced engine

70 hp, john deere 5030ht014 3.01 five cylinder turbo diesel engine, one engine cover side panel **missing**

Engine compartment fire **damage**, john deere pe5030 four cylinder turbo diesel engine, lift arm cylinder pins removed, but included

### VADER Sentiment Scores

{'neg': 0.254, 'neu': 0.746, 'pos': 0.0, 'compound': -0.70}

{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}

{'neg': 0.121, 'neu': 0.879, 'pos': 0.0, 'compound': -0.296}

{'neg': 0.183, 'neu': 0.817, 'pos': 0.0, 'compound': -0.4215}

# Image Annotation

[View instructions](#)

**Instructions:** Given an image, answer the following questions.

- If your answer to the first question is "Yes", a follow-up question will pop out. Otherwise, please continue to the second question.
- Please click on "**View instructions**" before moving on to your task.



1. Does this equipment's bucket contain rust?

☐ Yes ☐ No ☐ This equipment has no bucket.

2. Use a scale of 1 to 10 to describe how much rust the body of equipment has (please only take in account the body, not the bucket).

*1 means 'barely any rust' and 10 means 'rust all over the body'.*

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐ 8 ☐ 9 ☐ 10

[Submit](#)

## Sample 100 images



13 questions/image



3 workers/question



\$ 83.94 in total

## 13 questions

*Yes-no & Quantitative*

Background

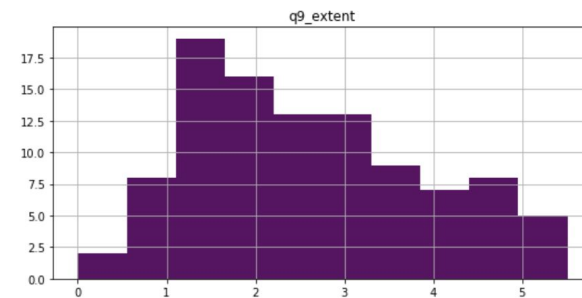
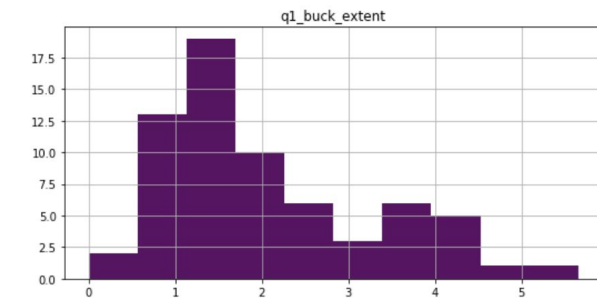
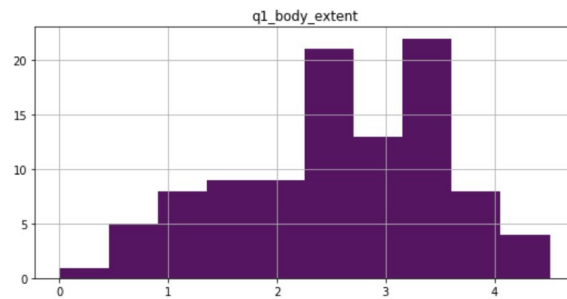
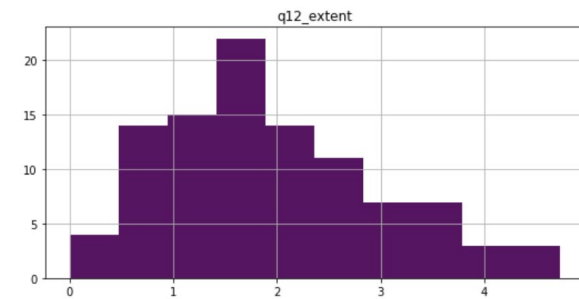
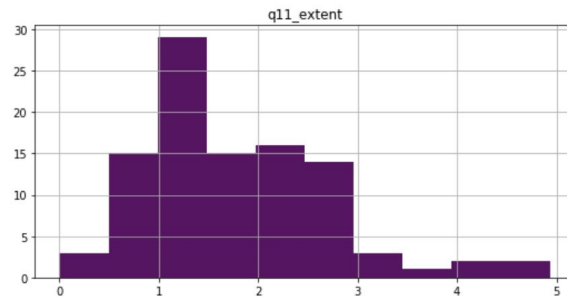
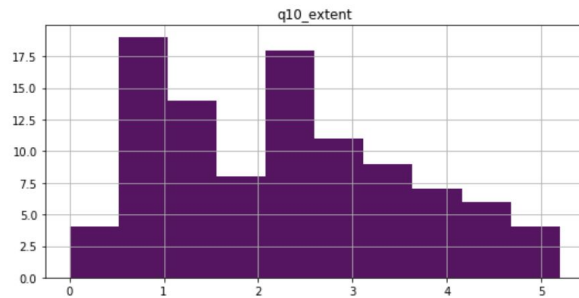


Rust extent

Brightness of color

Dirt level





## Annotation Quality:



Except for body rust extent, all other annotations are within 2-3 std dev away.

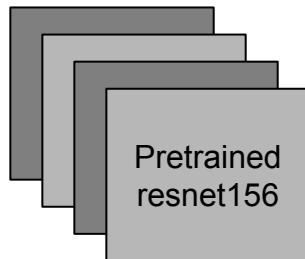
Distribution of Standard Deviations of All Numerical Answers for Each Image

# Final Model

Image



Freeze + Fine-tune



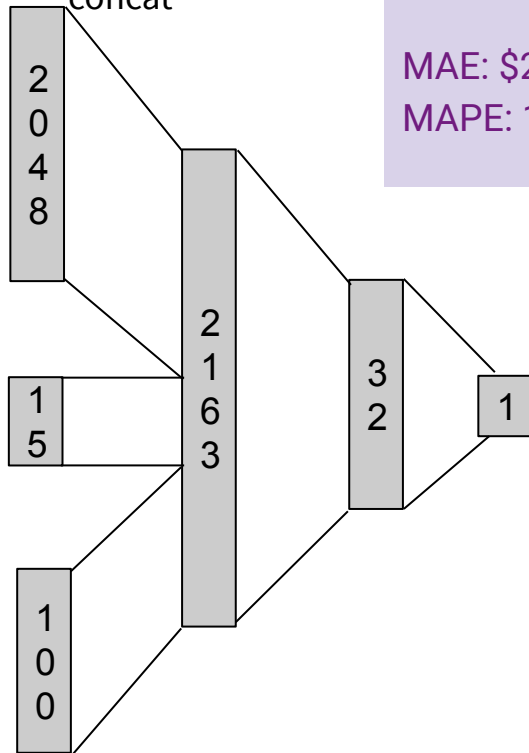
Tabular (+ Annotation)

Year  
Make  
Mileage  
Colorfulness  
etc.

Text

..., new factory remanufactured head, new ...

concat



Price

Performance:

MAE: \$2541.85

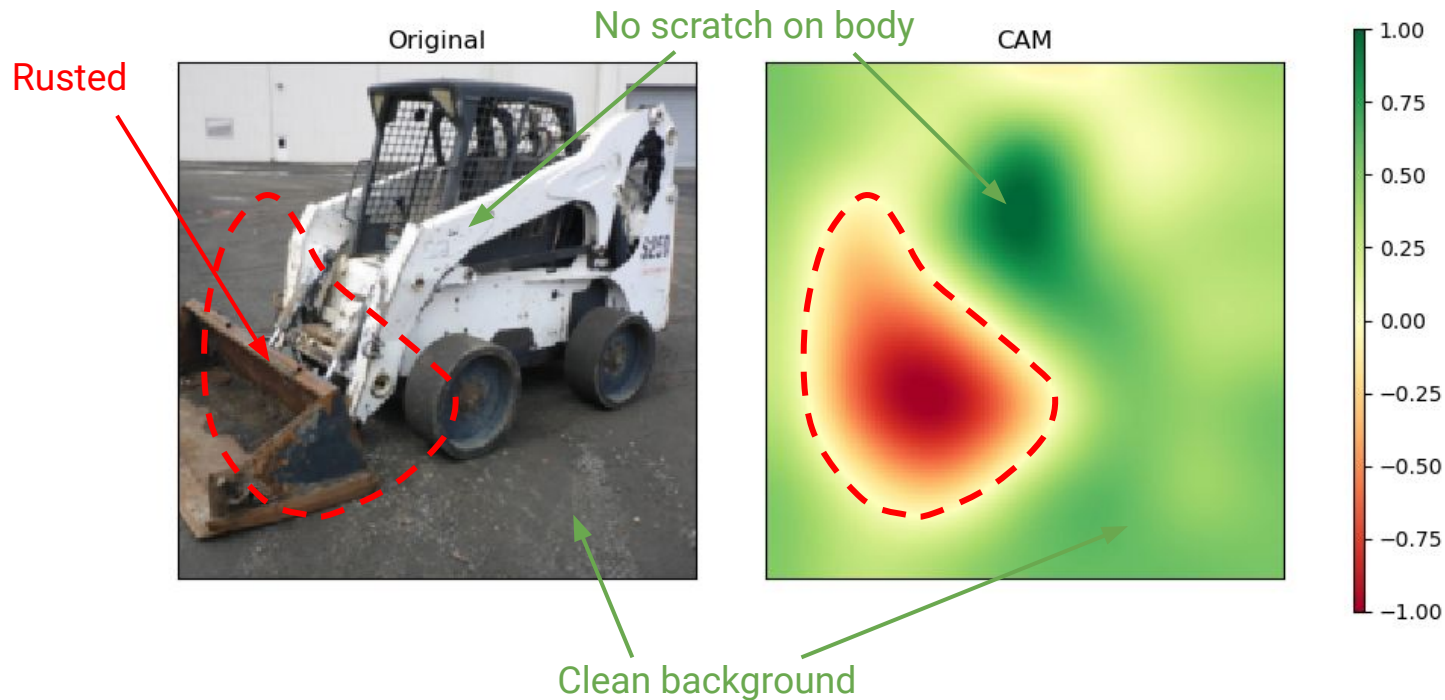
MAPE: 19.06%

# Interpretability - Images

- Hard to generate quantitative interpretation on images
  - without enough human annotations
- Try to qualitatively interpret images
  - Indicate which part of the image is driving up/down the price

# Interpretability - Attention Map

Real price: 8000 ~ Predicted: 9852



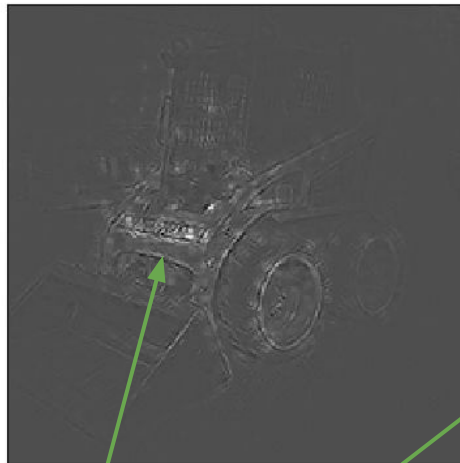
# Interpretability - Saliency Map



$$\frac{\partial \text{price}}{\partial \text{image}} =$$

Real price: 15000 ~ Predicted: 11249

Monochromatic



Colorful



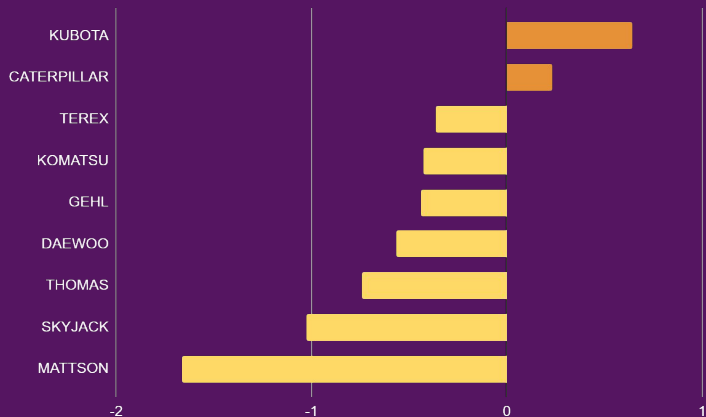
Clear brand logo and clean body

Model	Parameters	Sample Size	R^2	MAE	Model Comparisons
MLR	Hours_final, age_at_sale	6167	0.392	4076	
MLR	Hours_final, age_at_sale, parts_sentiment	6167	0.395	4062	
MLR	Hours_final, age_at_sale, colorfulness_score	6167	0.396	4047	
MLR	Hours_final, age_at_sale, month_of_sold_date	6167	0.401	4066	
MLR	Hours_final, age_at_sale, make	6167	0.434	3926	
MLR	Hours_final, age_at_sale, make, month_of_sold_date, colorfulness_score, parts_sentiment	6167	0.442	3902	
H2O_DRF	Hours_final, age_at_sale, make, month_of_sold_date, colorfulness_score, parts_sentiment	6167	0.489 (MSE)	3391	
MLR	Hours_final, age_at_sale	96	0.431	5384	
MLR	Hours_final, age_at_sale, make	96	0.570	4998	
MLR	Hours_final, age_at_sale, make, mturk	96	0.633	Unstable Because of Overfitting	
MLR	Hours_final, age_at_sale, make, mturk, parts_sentiment, colorfulness	96	0.676		Model Comparisons
MLR	Hours_final, age_at_sale, make, mturk, parts_sentiment, colorfulness, month_sold	96	0.802		
H2O_DRF	Hours_final, age_at_sale, make, mturk, parts_sentiment, colorfulness, month_sold	96	0.735 (MSE)		

## Brand Premium

Final selling price is on log scale

\* chart is based on coefficients of MLR



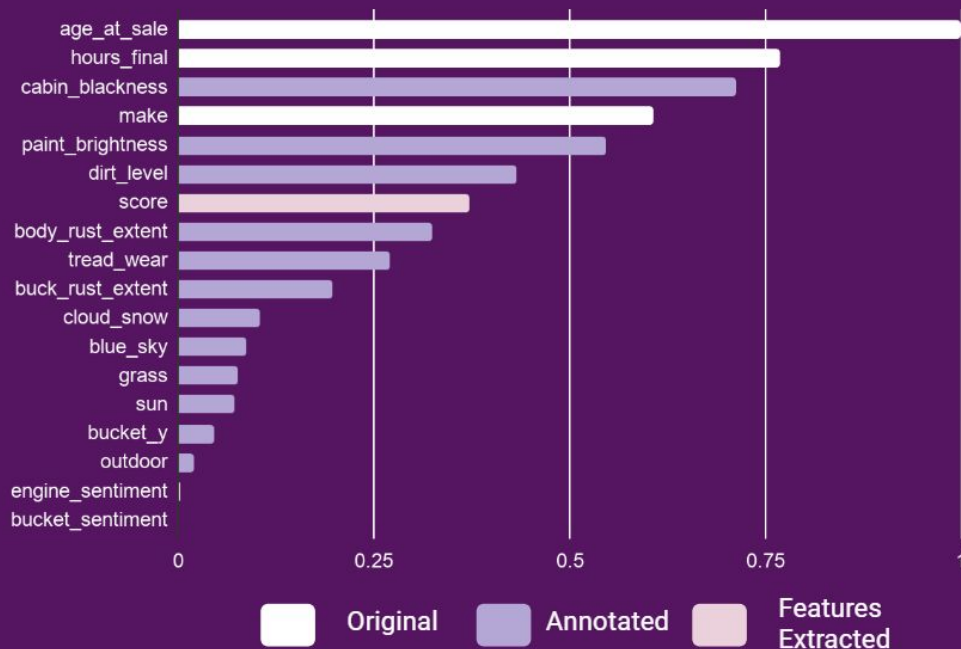
## Seasonality Influence on Sales Price

❖ Oct, Apr: Positive influence

❖ Jan, Sep: Negative influence

## Top Feature Importance

\* Chart is based on distributed random forest



# Quantitative Interpretation



<https://skidsteer-interpret.herokuapp.com/>

**Interactive Visualizations**



## Summary

- ❖ Interpretable features  
(machine and human)
- ❖ Price prediction



## Recommendations

- ❖ Image annotation  
(MTurk)
- ❖ Vehicle cleanliness

**Thank you!**

Yifei Wang & Bingying Liu

## II. Feature Extraction - Image Colorfulness

- Haslera and Susstrunk (2003)
- They ask people to rate images using 7 categories of colorfulness
- Propose a metric that correlates to 95.3% of the experiment data
- ***Opponent color space representation***

$$Rg = R - G$$

$$Yb = (1/2) (R + G) - B$$

$$\sigma_{rgyb} = \sqrt{\sigma^2_{rg} + \sigma^2_{yb}}$$

$$\mu_{rgyb} = \sqrt{\mu^2_{rg} + \mu^2_{yb}}$$

$$C = \sigma_{rgyb} + 0.3 * \mu_{rgyb}$$